Color Texture Classification under Different Illuminations Using Rank Correlation Matrices

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ABSTRACT: Color has been shown to be useful in the context of texture classification. However, since under different illuminations color is not stable, color invariant descriptors should be defined when the illumination of the query is unknown. In this paper, we propose to characterize color textures by analyzing the rank correlation of color planes between pixels locally close to each other. Thus, considering one distance and one direction in the image space, we obtain a correlation measure which i) is related to the colors of the pixels, ii) is illumination invariant, iii) represents the spatial interactions between different color components of neighbored pixels. Furthermore, we show how this measure can be very fast extracted from co-occurrence matrices. The discriminative power of this descriptor is assessed on a public color texture database.

INTRODUCTION: In this paper, we specifically address the problem of color texture classification across illumination changes. For this purpose, we consider images of color textures acquired with the same viewpoint and the same scale factor but under three different illuminations [33]. In this context, there exist different approaches for color texture description [10, 4, 1, 8, 21, 31, 26, 29, 35, 7, 22, 9, 16, 25, 4, 15, 11, 14, 20]. For example, the structural approach consists in analyzing the relative positions of features extracted from the image [12]. One other approach tries to model the spatial repartition of the colors in the image. In this aim, one can use Markov Random Fields [30, 27] or Local Binary Pattern [32, 31].

1.2 Rank correlation from co-occurrence matrices: A 2D co-occurrence matrix $M^k_{d,o}[I]$ of an image $I$ can be considered as an array of cells indexed by color component levels [26]. The cell $M^k_{d,o}[I](u,u')$ indicates the number of times that, in the image $I$, a pixel $P'$ whose level $c^k(P')$ is equal to $u'$, is located at the distance $d$ with orientation $o$ from a pixel $P$ whose level $c^k(P)$ is equal to $u$. Given a distance $d$ and an orientation $o$, a color image $I$ is characterized by 6 co-occurrences matrices: $M^{R,R}_{d,o}[I]$, $M^{G,G}_{d,o}[I]$, $M^{B,B}_{d,o}[I]$, $M^{R,G}_{d,o}[I]$, $M^{R,B}_{d,o}[I]$ and $M^{G,B}_{d,o}[I]$. Thus, considering $nd$ different distances $d_i$, $i = 1, ..., nd$ and $no$ different orientations $o_i$, $i = 1, ..., no$, each texture is characterized by $6noxno$ co-occurrence matrices. Considering the red and the green components, the Kendall's $\tau$ [23] represents the mean rank correlation between the red and the green levels of all pixels without taking into account the spatial interaction between the pixels in the image. In order to compensate this drawback, we propose to measure the mean rank correlation between the red level of a pixel and the green levels of all pixels which are located at a distance $d$ from this pixel according to the orientation $o$. From the definition of the Kendall’s $\tau$ [23], can be evaluated this measure by considering pairs of occurrences rather than pairs of pixels. As illustration, we consider in an image, one occurrence of pixels for a particular distance $d$ and a particular orientation $o$. This occurrence $O^{c_1}_{d,o}$ is constituted by a pair of pixels $P_1, P_1'$ which are located at a distance $d$ from each other in the orientation $o$.

Then, we consider a second occurrence in the same image $O^{c_2}_{d,o}$ which is constituted by a pair of pixels $P_2, P_2'$. By extending the definition of concordant pairs of pixels to pairs of occurrences, we can say that the pair of occurrences $O^{c_1}_{d,o}, O^{c_2}_{d,o}$ is a concordant pair according to the red and green components, if the red and green levels of the pixels in the two occurrences are ordered in the same manner, i.e. if $c^R(P_1) < c^R(P_2)$ and $c^G(P_1') < c^G(P_2')$, or if $c^R(P_1) > c^R(P_2)$ and $c^G(P_1') > c^G(P_2')$. Otherwise, if these occurrences are such as $c^R(P_1) < c^R(P_2)$ and $c^G(P_1') > c^G(P_2')$, or such as $c^R(P_1) > c^R(P_2)$ and $c^G(P_1') < c^G(P_2')$, the pair of occurrences is called discordant. The advantage of this correlation measure is that it can be very fast extracted from a 2D cooccurrence matrix. Indeed, we show below that the numbers of concordant and discordant pairs of occurrences can be obtained from the corresponding co-occurrence matrix. We consider the red-green matrix $M^{R,G}_{d,o}[I]$. The cell $ci$ in the figure 2 represents the number of time that, in the image $I$, a pixel $P'$ whose level $c^R(P')$ is equal to $r$, is located at the distance $d$ for the orientation $o$ from a pixel $P$ whose level $c^G(P)$ is equal to $g$. From the definition, we know that these occurrences constitute discordant pairs with the occurrences characterized by red levels lower than $r$ and green levels higher than $g$. The cells associated with these occurrences constitute the surface denoted $DISC_i$ in the figure 2. Note that we consider only the occurrences characterized by a green level higher than $g$ so that each occurrence pair is accounted only once in the evaluation of $S$. Consequently, the number of discordant pairs associated with the cell $ci$ in the figure 2 is:
We propose to use a similar approach as Bay [5] in order to speed-up this evaluation. Indeed, we propose to evaluate the top-right integral co-occurrence matrix \( M^{R,G}_{d,o}[I] \) from the matrix \( M^{R,G}_{d,o}[I] \). This integral matrix is evaluated as:

\[
M^{R,G}_{d,o}[I](r,g) = \sum_{n_r=0}^{L-1} \sum_{n_g=0}^{L-1} \frac{M_{d,o}[I](n_r,n_g)}{n_r + n_g + 1},
\]

for all \( r,g \in [0:L-1] \). This top-right integer matrix is used for the calculation of the numbers of discordant pairs associated with all the cells \( c_i \) so that equation becomes:

\[
discordant(c_i) = M^{R,G}_{d,o}[I](r,g) \times M^{R,G}_{d,o}[I](r,g).
\]

Thus, by this way, the evaluation of the number of discordant pairs is very fast. In the same way, we can evaluate the number of concordant pairs associated with the cells \( c_i \):

\[
concordant(c_i) = M^{R,G}_{d,o}[I](r,g) \times M^{R,G}_{d,o}[I](r,g),
\]

where \( M^{R,G}_{d,o}[I] \) is the bottom-right integer matrix deduced from the matrix \( M^{R,G}_{d,o}[I] \) thanks to the following equation:

\[
M^{R,G}_{d,o}[I](r,g) = \sum_{n_r=r-1}^{L-1} \sum_{n_g=g+1}^{L-1} M^{R,G}_{d,o}[I](n_r,n_g).
\]

The number in the cell \( c_i \) of this bottom-right matrix is the sum of the numbers in the cells which constitute the surface denoted \( \text{CONCi} \) in figure 2. Thus, for each cell \( c_i \) in the matrix \( M^{R,G}_{d,o}[I] \), we obtain very fast the numbers of concordant and discordant pairs by this way. The value of \( S \) is just deduced from the sum of the differences between the number of concordant pairs and the number of discordant pairs for all the cells:

\[
S = \sum_{c_i} concordant(c_i) - discordant(c_i).
\]

By this way, from each matrix \( M^{k,k'}_{d,o} \), we extract the mean rank correlation between the color components \( k \) and \( k' \) of pixels located at a distance \( d \) from each other for an orientation \( o \). Thus, a color texture is characterized by \( 6 \times ndxno \) rank correlation measures, i.e. \( 6 \times ndxno \) real values. In order to compare the contents of two different textures, we propose to use the Euclidean distance between the vectors constituted by the \( 6 \times ndxno \) rank correlation coefficients. So, we have just shown that the Kendall rank correlation between pixels located at a particular distance in a particular orientation can be very fast extracted from the corresponding co-occurrence matrix. Note that the Kendall rank correlation is invariant across illumination changes whereas the co-occurrence matrices in the RGB space are very
sensitive to illumination changes. Thus, the propose features do not require any color invariant transformation before being extracted.

The next section assesses the performance of this feature in the case of color texture classification across illumination changes.

1.3 Experiments and results: The outex database is used for testing [33] (http://www.outex.oulu.fi). This database contains color images from textures acquired under different conditions. Particularly, the subset called Outex_TC_00014 contains images of 68 different textures, each one being acquired under one of three available illuminants: 2300K horizon sunlight, 2856K incandescent CIE A light source or 4000K fluorescent TL84. In order to compare our color texture descriptor with other ones, we propose to use the classification process as those used by recent papers [2, 3, 31]. Thus, the used classifier is the k-NN classifier with k=3. The training set is constituted by sample images of each texture illuminated by incandescent light. For this, each image is divided into 20 non-overlapping sub-images, each of size 128 x 128 pixels, producing 1360 training images since the size of the original image is 746 x 538 pixels. The test set is constituted by the images acquired under the two other illuminants (horizon sunlight and fluorescent TL84), once again with 20 sub-images per texture. For each illumination source, 1360 images are available, making a total of 2720 test images. The only difference between the paper from Hafiane [2] and the papers from Handbury [3] and Mäenpää [31] is that Hafiane reduce the number of textures from 68 to 24. So, we will first test our method on the 24 textures chosen by Hafiane and then we will use the complete outex_TC_00014 database in order to compare our results with those provided by Handbury and Mäenpää. Table 1 presents the classification rates obtained by our descriptors on the reduced database (24 classes). Our descriptor is called $SC\tau'$ (SaptioColorimetric Kendall’s $\tau$ [23]) in this table. Furthermore, Hafiane [2] provides the performance of the following texture descriptors on this reduced database:

- Median Binary Pattern [2], called MBP in table 1,
- Local Binary Pattern [32], called LBP in table 1,
- Haralick parameters extracted from gray-level cooccurrence matrices [29], called GLCM in table 1,
- Gabor filter [34], called Gabor in table 1,
- Gaussian Markov Random Field [28], called GMRF in table 1.

In Hafiane’s paper, all these descriptors are extracted from gray-level images. In table 1, for each tested descriptor, we add the dimension of the feature vector. This information can be interesting for time processing considerations. Indeed, in the context of color texture classification (or recognition), the time required for classifying a query texture is directly related to the dimension of the used feature vector. Considering our descriptor, we have selected 4 directions from 0 to 135 and 5 distances from 5 to 20. Thus, for one sample image, we extract $6\times4\times5 = 120$ Kendall rank correlations.

Table 2 presents the classification rates provided by our descriptors on the complete database outex_TC_00014 (68 classes). For comparison, we use the results provided by Handbury [3] and by Mäenpää [31] on this database. Handbury proposed to use standard morphological texture characterisation tools such as variogram and granulometry. Applying to color images, the variogram represents the evolution of the differences between the color of a pixel and the colors of the pixels located at a particular distance in a particular direction while the granulometry is the ratio between the color components of a pixel in the original image and the color components of this pixel after applying a color opening or closing with a structuring element of increasing size. These morphological transformations are
applied in the RGB and CIELAB color spaces and on the single L* component of the CIELAB color space. The results provided by these descriptors are reported in table 2: \( VRGB, VLab \) and \( VL* \) for variogram and \( GRGB, GLab, GL* \) for granulometry. Furthermore, Handbury proposed to use an illumination-invariant normalization similar to the histogram equalization proposed by Finlayson [18]. Thus, in table 2, we report the classification results provided by the variograms and granulometries after applying this illumination invariant normalization on the outex_TC_00014 database: \( V_{invRGB}, V_{invLab}, V_{invL*}, G_{invRGB}, G_{invLab} \) and \( G_{invL*} \). In his paper, Mäenpää [31] also presents classification rates on the outex_TC_00014 database provided by some descriptors such as:
- Color histogram evaluated after applying the illumination invariant normalization proposed by Finlayson [19] \( (Histoinv) \),
- Color ratio histograms obtained from the illumination invariant normalization proposed by Funt [20] \( (CR histo) \),
- Multi-resolution Opponent Color Gabor \( (Opp Gabor) \),
- Multi-resolution grays-sale and color \( (L*a*b*) \) LBP \( (Multi gray LBP \) and \( Multi Lab LBP) \).

From tables 1 and 2, we notice that the proposed spatiocolorimetric rank correlation measure provides promising results in the context of color texture classification. Indeed, the classification rate obtained on the reduced database is almost perfect and this obtained on the complete outex_TC_00014 database is higher than the rates obtained by well-known approaches. Furthermore, the proposed descriptor is compact comparing with descriptors which provide similar results. Indeed, only 120 values are required to classify most of the 68 color textures acquired under different illuminations.

2. CONCLUSION: In this paper, we have proposed a color descriptor designed for the classification of textures across illumination changes. This descriptor analyzes the rank correlation measures between different color components of pixels located at a particular distance from each other in a particular direction. Thus, it accounts both the colors of the pixels and their spatial interactions. We have shown that this measure can be very fast extracted from the color co-occurrence matrices of the considered image. This extraction does
not require any color normalization as pre-processing step since it has been shown that the rank measure of the pixels are coarsely preserved in case of illumination changes. Furthermore, the proposed descriptor is very compact comparing with descriptors which provide similar classification rates. This compactness is very interesting for time processing considerations. We have assessed the performance of this descriptor on a public database showing promising results in the context of color texture classification across illumination changes.

REFERENCES: